2.1 Ventricular arrhythmia detection

Life threatening arrhythmias are Ventricular Tachycardia (VT), Supra Ventricular Tachycardia (SVT), Ventricular Fibrillation (VFIB), and Ventricular Flutter (VF). Detecting ventricular arrhythmias is a difficult task in arrhythmia monitoring system and in automated external defibrillator (AED). It is so because the ECG signal frequency distribution of this life threatening arrhythmia changes with prolonged duration [6]. Missing arrhythmias in ECG and false positive detection in defibrillator may lead to patient’s death and so most efficient techniques are required to detect cardiac arrhythmia signals from normal ECG signal.

2.1.1 Ventricular arrhythmia ECG signals

Ventricular tachycardia (VT) is a rapid heartbeat that starts in the ventricles. Ventricular tachycardia can occur without heart disease. If left untreated, some forms of ventricular tachycardia may get worse and lead to ventricular fibrillation, which can be life-threatening. Supra ventricular tachycardia (SVT) means that from time to time your heart beats very fast for a reason other than exercise, high fever, or stress. During an episode of SVT, the heart’s electrical system doesn't work right, causing the heart to beat very fast. The heart beats at least 100 beats per minute and may reach 300 beats per minute. After treatment or on its
own, the heart usually returns to a normal rate of 60 to 100 beats a minute. Ventricular flutter is an arrhythmia, more specifically a tachycardia affecting the ventricles with a rate of over 200 beats/min. It is characterized on the ECG by a sinusoidal waveform without clear definition of the QRS and T waves. It has been considered as a possible transition stage between ventricular tachycardia and fibrillation, and is a critically unstable arrhythmia that can result in sudden cardiac death. Ventricular fibrillation (VFIB) is a condition in which there is uncoordinated contraction of the cardiac muscle of the ventricles in the heart, making them quiver rather than contract properly. While there is activity, perhaps best described as "writhing like a can filled with worms" it is undetectable by palpation (feeling) at major pulse points of the carotid and femoral arteries especially by the lay person. Scar tissue may form in the muscle of the ventricles days, months, or years after a heart attack. This can lead to ventricular tachycardia. Normal ECG can identify the ventricular tachycardia, it provides most useful information.

Because ventricular tachycardia can occur intermittently and may not always be captured by an ECG at the doctor's office, so it is required to use a portable EKG to record heart rhythm on a continuous basis, usually over a 24-hour period. This is referred by several names, including ambulatory electrocardiography, ambulatory EKG, Holter monitoring, 24-hour EKG, or cardiac event monitoring.

Sustained tachycardia requires immediate treatment. It may need CPR or a shock from an automatic defibrillator (AED). To prevent the arrhythmia from recurring, it may be needed to take anti arrhythmic medicines. But these medicines may have side effects, and doctors often recommend a type of permanent pacemaker, called an implantable cardioverter defibrillator (ICD). This device is placed under the skin in your chest and continuously monitors your heart's rhythm. If ventricular
tachycardia occurs, the ICD applies an electrical shock to the heart to restore a normal rhythm. After a normal rhythm is restored, the device goes back to continuous monitoring mode. Sometimes, both medicines and an ICD are necessary.

Ventricular fibrillation is a medical emergency that requires prompt basic life support and advanced cardiac life support (BLS/ACLS) interventions because if arrhythmia continue for more than a few seconds, it will likely degenerate further into asystole (a flat ECG with no rhythm- which is usually not responsive to therapy unless there is still some residual fine VF rhythm left or the patient is otherwise lucky and is treated very quickly); after this, within few minutes blood circulation will cease, and sudden cardiac death (SCD) may occur in a matter of minutes and/or the patient could sustain irreversible brain damage and possibly be left brain dead.

2.2 Detection Techniques

There are a variety of automatic detection techniques that are available to find these arrhythmias in the market to diagnose properly. Still research is going on to find 100% accuracy because if any misleading, leads to death.

In ICD and defibrillators, many algorithms are used to identify these arrhythmias. Threshold crossing intervals algorithm, Auto correlation algorithm, sequential hypothesis algorithm, VF filter algorithm, spectral algorithm, complexity measure algorithm, signal comparison algorithm, Tompkins algorithm, wavelet based algorithm, Li algorithm, and wavelet and neural network based algorithms etc. are used to identify the arrhythmias in heart. With the recent advancement of technology, the wavelet technique is emerging into Cardiology. Wavelet detection techniques are more powerful and truthful. The following
detection techniques are discussed:

- **Tompkins algorithm**
- **Spectral algorithm**
- **Wavelet based algorithms to detect ECG points**
- **Ventricular Arrhythmia Detection using Wavelet Transforms**

### 2.2.1 Tompkins algorithm
Pan J Tompkins (1985) derived an algorithm to detect QRS complex search, it identifies QRS, from which other points can be easily identified. It uses slope, amplitude and width information to carry out this task. After pre-processing, the ECG signal is band filtered by a low pass filter and a high pass filter to reduce interference and high frequency noise. Then, the signal is differentiated to provide the QRS complex slope information. The difference equation for the slope $y(j)$ of the ECG data $x(j)$ reads

$$y(nT) = \frac{1}{6T} (-x(nT - 2T) - 2x(nT - T) + 2x(nT + T) + x(nT + 2T) - x(nT + T))$$

(2.1)

Where $T$ is the sampling period of the ECG signal. Afterwards, the signal is squared to make all data points positive. Moving window integration with a window width of 150 ms (e.g., 54 points at a sampling rate of 360 Hz) is applied. Thresholds are set up to detect QRS complexes. This algorithm uses a dual threshold technique and a search back for missed beats. If the number of found QRS complexes is smaller than $l_0 = 2$ or higher than $l_1 = 32$, the ECG segment is classified as VF [25].

### 2.2.2 Spectral algorithm [SPEC]
Barro et al (1989) used different frequency domain techniques and he analyses the energy content in different frequency bands by means of Fourier analysis [6]. The ECG of most normal heart rhythms is a broadband signal with major harmonics up to about 25 Hz. During VF, the ECG becomes
concentrated in a band of frequencies between 3 and 10 Hz. After pre-processing, each data segment is multiplied by a Hamming window and then the ECG signal is transformed into the frequency domain by fast Fourier transform (FFT). The amplitude is approximated in accordance with Ref [6] by the sum of the absolute value of the real and imaginary parts of the complex coefficients. Let O be the frequency of the component with the largest amplitude (called the peak frequency) in the range 0.5 - 9 Hz. Then amplitudes whose value is less than 5% of the amplitude of O are set to zero. Four spectrum parameters are calculated, the normalized first spectral moment \( M \)

\[
M = \frac{1}{\Omega} \sum_{j=1}^{J_{\text{max}}} a_j w_j
\]

\( J_{\text{max}} \) being the index of the highest investigated frequency, and \( A_1, A_2, A_3 \). Here \( w_j \) denotes the \( j \)-th frequency in the FFT between 0 Hz and minimum of (20 \( \Omega \), 100 Hz) and \( a_j \) is the corresponding amplitude. \( A_1 \) is sum of amplitudes between 0.5 Hz and \( \Omega/2 \), divided by the sum of amplitudes between 0.5Hz and minimum of (20 \( \Omega \), 100 Hz). \( A_2 \) is sum of amplitudes between 0.7 \( \Omega \) and 1.4 \( \Omega \), divided by the sum of amplitudes between 0.5Hz and minimum of (20 \( \Omega \), 100 Hz). \( A_3 \) is sum of amplitudes between 0.6 Hz bands around the second to eighth harmonics (2\( \Omega \) - 8\( \Omega \)), divided by the sum of amplitudes between 0.5Hz and minimum of (20 \( \Omega \), 100 Hz).

VF is detected if \( M \leq M_0 = 1.55, A_1 < A_{1,0} = 0.19, A_2 \geq A_{2,0} = 0.45 \) and \( A_3 < A_{3,0} = 0.09 \).

The critical threshold parameters to obtain the Receiver Operating Characteristic (ROC) is \( A_{2,0} \), the other threshold parameters (\( A_{1,0}, A_{3,0}, M_0 \)) being kept constant.

### 2.2.3 Wavelet based algorithms to detect ECG points
Frequency based techniques for classification of cardiac rhythms offer more promising prospects as they are more robust to noise in comparison to time domain techniques and
present a more effective model of the QRS complex. However, use of time-frequency decomposition of the ECG signal using the wavelet transform offers a better alternative than the application of Fourier transform for beat classification due to the non-stationary nature of the ECG signal. The wavelet transform is one of the powerful tools to analysis the non-stationary cardiac signal for the detection of Cardiac arrhythmias. It is a promising technique for time frequency analysis. The Wavelet transform (WT) can be used to decompose ECG signals into elementary building blocks and can characterize the local regularity in time and frequency of the signal.

G. H. Friesen et al (1990) discussed elaborate analysis on different algorithm in noise condition to detect QRS points in ECG waveform. He compared all aspects and has given detailed reports [26].

Li et al (1995) discussed a detailed analysis of ECG signals based on wavelet analysis [27]. Senhadji et al (1995) compared the ability of three different wavelet transforms (Daubechies, spline and Morlet) to recognise and describe isolated cardiac beats [28]. Sahambi et al (1997(a) and 1997(b)) employed a first order derivative of the Gaussian function as the wavelet for the characterization of ECG waveforms. They then used modulus maxima-based wavelet analysis employing the Dyadic Wavelet Transform to detect and measure various parts of the signal, specifically the location of the onset and offset of the QRS complex and P and T waves[29-30]. Sahambi et al (1997) showed that the algorithm performed well in the presence of modeled baseline drift and high frequency noise added to the signal. They used the method to determine timing intervals of the ECG signal including the widths of the QRS complex, T and P waves, PR, ST and QT interval. The measurement of these intervals gives the relative position of the components in the ECG which is important in delineating the electrical activity of the heart. Improvements to the technique are described in Sahambi et al (1998)[31]. Sivannarayana and Reddy (1999) have proposed the use of both launch points and wavelet extrema to obtain reliable amplitude and duration parameters from the ECG [32]. Kadambe
et al (1999) have described an algorithm [33] which finds the local maxima of two consecutive Dyadic Wavelet scales, and compared them in order to classify local maxima produced by R waves and by noise.

R wave detectors are extremely useful tools for the analysis of ECG signals. They are used both for finding the fiducial points employed in ensemble averaging analysis methods, and for computing the R-R time series from which a variety of heart rate variability (HRV) measures can be extracted. Both these techniques rely on the accurate determination of the temporal location of the R wave. There are currently a number of QRS detection algorithms available which use a variety of signal analysis methods. The most common of these are based on signal matched filters or time-frequency decomposition methods. Other less common methods have also been proposed including neural networks, genetic algorithms and syntactic methods (Köhler et al, 2002) [34]. Recently, wavelet-based QRS detection methods have been suggested by a variety of groups including Li et al (1995) who proposed a method based on finding the modulus maxima larger than a threshold obtained from the pre-processing of preselected initial beats. In Li et al’s method [27], the threshold is updated during the analysis to obtain a better performance. This method has a post-processing phase in which redundant R waves or noise peaks are removed. The algorithm achieves a good performance with a reported sensitivity of 99.90% and positive prediction value of 99.94% when tested on the MIT/BIH database [35]. Ranith et al (2002) used similar technique to detect myocardial ischemia [36]. Shyu et al (2004) have extended the algorithm of Li et al to detect ventricular premature contractions (VPCs). By incorporating a fuzzy neural network, they achieved a 99.79% accuracy for VPC classification [37]. Martinez et al (2004) also utilise the algorithm of Li et al applying a dyadic wavelet transform to a robust ECG delineation system which identifies the peaks, onsets and offsets of the QRS complexes, P and T waves [38].
Wavelet energy scalogram was used by Meste et al (1994) as a method of highlighting ventricular late potentials and observing temporal and frequency variability in the ECG from beat to beat [39]. More recently, members of the same group have proposed a VLP detection method based on the analysis of the behavior of the wavelet energy density surface in a selected time-frequency region occurring beyond the end of the QRS complex (Lewandowski et al, 2000) [40]. They evaluated their method on a group of 106 post infarction patients composed of 62 with documented monomorphic ventricular tachycardia and 44 without arrhythmia. Their results indicated that the method appears to be a useful tool for the detection of micro potentials indicating good diagnostic relevance for risk evaluation of cardiac arrhythmia. They report results of 85% sensitivity at 93% specificity for signals which were preprocessed using polynomial filtering. This result compared favorably with other methods of analysis including time domain, FFT and Auto Regressive methods. Wu et al (2001) have proposed a hybrid method which uses an artificial neural network to recognise VLPs from the (continuous) wavelet transformed signal. They report a sensitivity of 80% and specificity of 77% for the detection of beat-to-beat-based VLPs [41]. Romero-Lagarreta et al (2005) have extended the work of Li et al and Kadambe et al, utilising the continuous wavelet transform. Their CWT-based algorithm affords high time-frequency resolution which provides a better definition of the QRS modulus maxima curves[42]. Saritha et al (2008) have done ECG analysis using wavelet transform. [43]. V. S. Chouhan ( 2008 ) have used wavelet transform to detect QRS points using adaptive threshold techniques and same author used wavelet to remove baseline wandering of ECG signal .[44-45] . Josko (2007) used wavelet transform to analyze the ECG signal [46]. A. Pachauri et al (2009)[47] used wavelet technique to detect Are wave in ECG signals. Ruchita (2010) have used wavelet transform to detect QRS complexes [ 48].

### 2.2.3.1 Li algorithm

The Li algorithm (LI) [16] is based on wavelet analysis,
The wavelet transform of an ECG signal is calculated using the following equations

\[ S_{2^j}f(n) = \sum_{k \in \mathbb{Z}} h_k \, s_{2^j-1}f(n - 2^{j-1}k) \quad (2.3) \]
\[ W_{2^j}f(n) = \sum_{k \in \mathbb{Z}} g_k \, s_{2^j-1}f(n - 2^{j-1}k) \quad (2.4) \]

Here, \( S_{2^j} \) a smoothing operator and \( S_{2^0}f(n) = d_n \), \( d_n \) being the ECG signal. \( h_k \) and \( g_k \) are coefficients of a low pass filter \( H(w) \) and a high pass filter \( G(w) \), respectively. Scales \( 2^1 \) to \( 2^4 \) are selected to carry out the search for QRS complexes. QRS complexes are found by comparing energies from the ECG signal in the scale \( 2^3 \) with the energies in the scale \( 2^4 \). Redundant modulus maximum lines are eliminated and the R peaks detected. Different methods from Tompkins [25] are used to improve the detection quality:

**Method 1**

Blanking, where events immediately following a QRS detection are ignored for a period of 200 ms.

**Method 2**

Searching back, where previously rejected events are reevaluated when a significant time has passed without finding a QRS complex. If no QRS complex was detected within 150% of the latest average RR interval, then the modulus maxima are detected again at scale \( 2^3 \) with a new threshold. If the number of found QRS complexes is 0 or higher than 5 times the window length in seconds, the ECG segment is classified as VF. The critical threshold parameter to obtain the ROC is the number of found QRS complexes.

**2.2.4 Ventricular Arrhythmia Detection using Wavelet Transforms**
Ventricular tachy arrhythmias, and in particular ventricular fibrillation (VF), are the primary arrhythmic events in the majority of patients who present with sudden cardiac death. During ventricular fibrillation the lower chambers of the heart beat in an irregular fashion. Much work has been conducted over recent years into VF centered on attempts to understand the pathophysiological processes occurring in sudden cardiac death, predicting the efficacy of therapy, and guiding the use of alternative or adjunct therapies to improve resuscitation outcomes.

Many linear techniques have been developed to detect the arrhythmia. Probability Density Function technique is proposed by Langer et al. (1976) [49], Sequential Hypothesis Testing Algorithm was utilized by Thakor et al. (1994), and Chen (1996) [50], [51]. Analysis of Peaks in short term Auto Correlation Function by Chen and Thakor (1987) [52], Ripley (1989) used Rate and Irregularity Analysis [53], Correlation Waveform was utilized by Lin et al. (1988) [54], Four fast Template Matching Technique was utilized by Throne et al. (1991) [55], VF Filter Method has been used by Clayton and Kuo (1978) [56], [57], Spectral Analysis was used by Barro (1989) [6] and Time Frequency Analysis was utilized by Afonso (1995) [58].

Most of the researchers reported that these techniques are too difficult to implement and compute triggering time for Automated External defibrillator (AED’s) and Implantable Cardioverter Defibrillator (ICD’s). Normally the amplitude of ECG signal decreases as Ventricular Fibrillation (VFIB) duration increases and the frequency distribution changes with prolonged duration [59]. The limitations of the short term auto correlation function and time frequency analysis are due to detection of the features of such amplitude and frequency changes. The algorithms of, Sequential hypothesis testing, analysis of peaks in short term auto correlation function, rate and irregularity analysis, correlation waveform analysis, Four fast template matching technique are able to detect very few arrhythmias. These
above algorithms are not suitable for detecting all the Ventricular arrhythmias. Besides these linear techniques, many non-linear techniques also have been developed which utilize the non-linearity of ECG signal for detecting life threatening arrhythmias for short ECG episode duration by Zheng(1999) and Yan sun(2005)[60],[61]. However, there are still many problems requiring solution because of the computational demands. Most of the existing algorithms are difficult to detect a long ECG episode duration in a shorter period of time.

Minami et al. [1999] have proposed application of Fourier Transform (FT) based Frequency Domain techniques for classification of Supraventricular Rhythm, Ventricular Rhythm including Ventricular Tachycardia, Premature Ventricular Contraction, and Ventricular fibrillation[62]. This method achieves a Sensitivity/Positive Predictivity of ~98%. A related technique is the use of filter banks as given by Afonso et al. [1997] [63].

Addison et al, 2000[64] showed a global view of a long term VF signal in wavelet space, it contains an energy scalogram for a five minute period of pig VF followed by a 2.5 minute period of cardiopulmonary resuscitation (CPR). Addison et al, (2002(b)) [65] showed the pressure in the aorta and ECG corresponding to an episode of ventricular fibrillation in another porcine model.

Many researchers have used animal models in the study of VF. This allows laboratory study of this fatal arrhythmia, in particular the acquisition of long term VF data sets. The validity of this approach is questionable, both in terms of the underlying pathophysiology, and because significant interspecies differences in parameters such as median fibrillation frequency invalidate direct extrapolation to the human situation. Although, these models still provide important information on the long term aspects of VF much work has focused on the analysis of short term traces of pre-shock human VF obtained from out of hospital cardiac arrests acquired through modified defibrillator
devices. Coherent spiking structure has also been observed in these segments of human VF. The observation reveals that human VF, previously thought to represent this organised and unstructured electrical activity of the heart, does in fact contain a rich underlying structure hidden to traditional Fourier techniques (Addison et al, 2000; Watson et al, 2000)[66]. Building upon these results, a wavelet-based method for the prediction of the outcome from defibrillation shock in Human VF has been proposed by Watson et al (2004) [67]. An enhanced version of this method (Watson et al, 2005) employing entropy measures of selected modulus maxima achieves well over 60% specificity at 95% sensitivity for predicting a return of spontaneous circulation (ROSC). This is significantly better than current alternative techniques based on a variety of measures including Fourier, fractal, angular velocity, etc. The best of these typically achieves 50% specificity at 95% sensitivity. This enhancement is due to the ability of the wavelet transform to isolate and extract specific spectral-temporal features for use in the analysis [68].

Another approach employing Wavelet Transform has been formulated by Prasad et al. (2003)[69] which uses sym6 wavelets for classifying 12 different types of beats in the MIT-BIH Arrhythmia database with a reported accuracy of 96.77% through a Neural Network Classifier. Inan et al. (2006) have presented a method for detection of PVCs using wavelet transform coupled with a neural network classifier achieving an accuracy of over 95% on 40 files of the MIT-BIH Arrhythmia Database [70]. Yu et al. (2007) have presented a beat classification technique that extracts 11 features from wavelet decomposition sub-bands of an input ECG signal and applies a probabilistic neural network for classification of 6 types of beats from MIT-BIH Arrhythmia database achieving accuracy greater than 99%[71].

Amman et al (2005) used Hilbert transform to find Ventricular Fibrillation for Automated External Defibrillators. [72],[73].
Srinivasan et al (2002) has used auto regressive (AR) model coefficients[74]; and same used by Enign (2004) with higher-order cumulant and wavelet transform coefficient variances as features with a neuro-fuzzy classifier achieving an accuracy of 98% for 4 types of beats from the MIT-BIH Arrhythmia database [75]. Güler et al. (2005) have proposed a mixture of experts approach to discriminate five different types of beats with wavelet transform coefficients and lyapunov exponents of the ECG as features and have achieved an accuracy of ~98%[76].

Another technique proposed by Güler et al. (2005) uses statistical features such as mean of the absolute values, Average power and standard deviation of the coefficients in each sub-band along with ratio of absolute mean values of adjacent sub-bands extracted from the wavelet decomposition of the ECG signal with a cascaded neural network architecture for classification. This method has achieved an accuracy of ~97% in classifying four types of ECG beats (Normal, Congestive Heart Failure, Ventricular Tachycardia, Atrial fibrillation) from the MIT-BIH database [77]. Christov et al. (2005) [78] and Bortolan et al. (2005) [79] have used 26 morphological features extracted from the ECG and Vector Cardiogram (VCG) for the classification of PVC with a $k^{\text{th}}$ Nearest Neighbor Classifier and these papers illustrate the potential of using the $k^{\text{th}}$ Nearest Neighbor Classifier for beat classification in comparison to other classifiers. Niwas et al (2005) have utilized features such as heart beat intervals, RR-intervals and spectral entropy of the ECG signal along with a Neural Network classifier to reach an accuracy of 99.02% over the MIT-BIH Arrhythmia database [80].

Application of wavelet transform, principal component analysis (PCA) and several types of neural network structures in order to detect and classify different kinds of heart arrhythmias have been presented by Silipo et al 1998 [81].

principal components from the ECG signal for classifying 4 types of heart beats from the MIT-BIH arrhythmia database with an accuracy of 99.17% [84].


In this thesis an attempt is made to detect ventricular arrhythmias using wavelet based algorithms and mixture of Martinez [38] and Tompkinson algorithm [61] algorithm with wavelet function with automatic changing threshold levels. Here also reported about spectral response of ventricular arrhythmias. The basic description of the problem considered ventricular arrhythmia detection using wavelet transform is given in the next chapter.

### 2.2.4.1 Wavelet algorithm

The continuous wavelet transform of a signal \( f \in L^2 \) is defined by

\[
L_p^f(a, b) = \frac{1}{\sqrt{c_\psi|a|}} \int_R f(t) \psi^{t-b} \frac{a}{t} dt
\]  

(2.5)

where \( \psi \) is the mother wavelet, \( \psi \in L^2 \), and admissible,

i.e.,
\[ 0 < C_\psi = 2\pi \int_R \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \] (2.6)

Here, \( \hat{\psi} \) denotes the Fourier transform of \( \psi \).

\[ \psi(w) = \frac{1}{\sqrt{2\pi}} \int_R \psi(x) \exp(-iwx) dx \] (2.7)

The wavelet transform \( L_\psi f \) contains information about the frequency distribution as well as information on the time distribution of a signal.

The Fourier transform of \( L_\psi f \) is given by

\[ \widehat{L_\psi f}(a,b) = \sqrt{\frac{2\pi|a|}{C_\psi}} \psi(-aw) f(w) \] (2.8)

**WVL1**

A simple wavelet based algorithms (WVL1) operates like SPEC in the frequency domain. The idea of this first wavelet algorithm is the following: First, a continuous wavelet transform of the ECG signal is carried out using a Mexican hat as mother wavelet. Then a Fourier transform is performed. Now, the maximum absolute values are investigated in order to make the decisions for the defibrillation process. However, one can show that these maximum values are located on a hyperbola in the \((a, w)\) plane of the Fourier transform of the wavelet transform of the ECG signal, i.e., on a curve that has the representation \( aw = C \), \( C \) being a constant. The values on this curve in the \((a, w)\) plane are the Fourier transform of the ECG signal multiplied by a weight function \( g(w) \). Therefore, if one searches for the maximum values of in the \((a, w)\) plane of the wavelet transform, it is sufficient to search for the maxima of the weighted Fourier transform of the ECG signal. Since we are looking for maxima of the modulus of , we need to consider the maxima of only. In WVL1 the function is
handled exactly like the spectrum in the algorithm SPEC. The same spectrum parameters are calculated and also the thresholds for the decision have the same values like the algorithm in SPEC.

WVL2

This new method of detecting ventricular fibrillation uses a discrete wavelet transform. It is split into two parts.

(i) Finding VF

The first part uses the algorithm SPEC to search for typical VF properties in the ECG. If the algorithm decides that the ECG part contains VF, then the result is accepted as true and no further investigation is carried out. This procedure can be justified by the high specificity of the SPEC algorithm. If the algorithm yields that the ECG part is "no VF", a further investigation is carried out to confirm this result or to disprove it.

(ii) Discrete Wavelet Transform (DWT)

This part is only carried out, if the first part of the algorithm considers the ECG episode to be "no VF". In this case a discrete wavelet transform is applied, that searches for QRS complexes in the following way: The third scale of a discrete wavelet transform with 12 scales and a "Daubechies8" wavelet family is used. Numerical tests have shown that this scale makes it easiest to distinguish VF from "no VF". If the signal in the third scale has a value higher than a certain threshold, the according ECG part is considered as QRS complex. The threshold used in this investigation is set to 0.14max (ECG signal). Multiple peaks belonging to the same QRS complex are removed. If more than two but less than 40 QRS complexes are found within an 8 second episode, "no VF" is diagnosed. Otherwise the two spectral parameters $FSMN$ and $A2$ from the first part are investigated again. If $FSMN < 2.5$ and $A2 > 0.2$, the considered ECG part is diagnosed as VF.
The mentioned range for the number of found QRS complexes has the following reason: Sometimes, especially in ECGs with a high amount of noise, the DWT part makes wrong interpretations and "finds" QRS complexes also in QRS free episodes. Therefore, a minimal number of three QRS complexes is demanded to confirm the existence of QRS complexes. On the other side, if the DWT part "finds" more than 40 QRS complexes (equal to a pulse of 300beats per minute), the signal is likely to be VF, since such high sinus rhythms do not appear. The limits of the range were chosen from experiments with data. In WVL2 no IROC is calculated due to the special structure of the algorithm. Since it consists of two parts and the second part is not executed always, we do not have a single parameter that includes the calculations of both algorithm parts in every ECG segment. Hence we cannot calculate an IROC value. Using the parameters of the SPEC algorithm as an IROC parameter does not yield an ROC curve over the full range. Comparing the VF detection algorithms with two algorithms, that are originally used for QRS detection. The decision thresholds of these algorithms have been optimized to be suitable for Ventricular arrhythmia detection.